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A HYBRID NEURAL MODEL FOR TARGET RECOGNITION

BY A. FARSAIE J. J. FULLER T. TARR AND L. E. ELKINS

WEAPONS SYSTEMS DEPARTMENT

OCTOBER 1991

NAVAL SURFACE WARFARE CENTER

Dahlgren, Virginia 22448-5000 • Silver Spring, Maryland 20903-5000

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FOREWORD

An invariant pattern recognition methodology is presented. Recognition is based on a unique feature extraction technique and a newly developed Artificial Neural System (ANS). This target recognition approach demonstrates that using an ANS architecture, recognition can be obtained despite target orientation, size, or aspect angle.

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This technical report was reviewed by Mr. Kenneth F. Caudle, Head of the Advanced Weapons Division.

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ABSTRACT

The invariance principle is one of the important design consideration in target recognition. Some theoretical aspects of this principle were investigated. A new set of affine invariant features were developed. Geometrical examples are given, and features generated using this feature extraction technique are demonstrated.

A novel artificial neural network model was developed to analyze these features and perform classification of the targets. This network acts as a dynamic model to establish classes of targets in a nonlinear fashion.

Recognition is based on the combination of a unique set of features and the newly developed neural network model. This target recognition approach demonstrates that recognition can be obtained despite target orientation, size, or aspect angle.

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INTRODUCTION

Automatic, fast, and accurate target recognition is crucial to support the capabilities of on-board smart weapon systems which reduce the workload of crew members. It can also eliminate many of the errors introduced by humans whose situational awareness is degraded by an immense workload. Conventional target recognition methodologies are substantially limited when applied toward the solution of complex Navy problems. Despite the many advances in computer architecture and speed, there remain many problems in which human solutions are superior to computer solutions in terms of accuracy, adaptability, graceful degradation, generality, cost, and speed.

Automatic Target Recognition (ATR) is one of the key components of smart weapon systems. Current ATR systems cannot deal effectively with uncertainty as humans do, nor learn to produce better results as experience is gained. This is an important problem which has been the subject of considerable development over the past several years. The problem dictates the need for a very powerful system which is compact, distributed, fault tolerant, and robust. There are several issues to be concerned with in developing an ATR algorithm. Sample data representing possible variations of the target is desirable. The system should perform efficiently under occlusion and obscuration. Furthermore, the ATR system should be able to adapt to the addition of new targets to its database.

Biological information processing has continued to be an inspiring source for modeling a wide spectrum of signal and image understanding problems. The appeal of biological models for perceptual tasks has been enhanced by their strong potential for hardware implementation and by the shortcomings of conventional procedural models. Artificial Neural Systems (ANS) based on biological models have been widely proposed for recognizing patterns from sensor data. The benefits of using ANS technology for target recognition becomes apparent as one examines the process of developing a system to perform target recognition.

The objective of this report is to describe a new target recognition method. This methodology greatly increases the probability of recognizing targets from imaging sensor data using a new feature extraction scheme and a novel neural network model.

APPROACH

An effective target recognizer should be able to deal with variations in target signature within the appropriate look time, without a large measure of performance degradation. The features considered in classification should always be separable in feature space so that decisions may be made with a high degree of confidence.

Invariant target recognition involves two distinct processes. The first is to define a set of affine invariant features to be extracted from the targets of interest, and the second involves selecting an appropriate target recognition algorithm for use with the extracted features. Although binary images were used in this experiment, further study showed that grey-scale images also can be used with no significant decrease in the accuracy of the system.

FEATURE EXTRACTION TECHNIQUE

Image data used in this study were binary silhouettes from which features were extracted. The features extracted were similar to those described by Fuller (1990)[1] for identification of targets in two-dimensional (2-D) space. Features are as described below:

Let a binary target image be displayed in a n x n pixel grid and let P[i,j] denote the value "0" or "1" of the pixel in row i and column j of the image. Let $(\overline{X}, \overline{Y})$ denote the center of mass of the digitized target image. Then (i,j) and (k,l) are said to be "theta-neighbors" if and only if:

1. P[i,j] = P[k,l] = 1

2. $i = r\cos(\phi[1]) + \overline{X}$

   $j = r\sin(\phi[1]) + \overline{Y}$

   $k = r\cos(\phi[2]) + \overline{X}$

   $l = r\sin(\phi[2]) + \overline{Y}$

where $\phi[2] - \phi[1] = \theta$ and $r > 0$

Pseudo-Invariant features were constructed from theta-neighbors as follows:

Let {a[1],a[2],...,a[m]} be a set of distinct angles with $0 < a[i] < a[2] < \ldots < a[m] < 180$ for i=1,2,..,m; and

Let S[i] denote the number of a[i] neighbors in the image where it is required that $0 < r < \min\{n-\overline{X}, n-\overline{Y}\}$; with n being the size of the grid.

Then we define

$$F[i] = R_0^2/(R^2 * S[i])$$

where R is the radius of the smallest circle which can enclose the unknown target image; and R_0 is the radius of the smallest circle which could enclose the largest target during training.

It is apparent from the definition and the fact that the features are extracted with respect to the center of mass of the targets that {F[1],F[2],...,F[m]} form an invariant set under rotation and translation. To illustrate that they are invariant under scaling and to illustrate the power of the features in target identification, the set {S[1],S[2],...,S[m]} must be investigated more closely.

Closer inspection of the definition of S[i] shows that S[i] may be calculated by counting the number of 1's when the original image is "Anded" with an image obtained by rotating the original through an angle of a[i]. This is shown pictorially in Figure 1. Column 1 shows two simple objects A and B. Column 2 presents the two objects rotated by 10 and 90 degrees (counterclockwise), respectively. Column 3 combines the original objects, the rotated object, and the intersection which constitute the theta neighbor. Column 4 shows 10-degree and 90-degree neighbors superimposed on the original object. As described above, the features S[i] would be obtained by counting the pixels in the "pixel with theta-neighbor" areas.

The values for the number of pixels with 90-degree neighbors in Figure 1 are 650 for object A and 550 for object B. The number of pixels having 10-degree neighbors are 730 for object A and 640 for object B. This observation reveals that, by using theta-neighbors, one can distinguish between objects A and B at any angle of rotation and, despite any linear translation, by counting 90- and 10-degrees neighbors.

The regularity of the above objects might preclude the need for the use of theta-neighbors for classification. Other simpler features--such as height/width ratios or number of vertices--might be easier to extract and just as effective as theta-neighbors. In Figure 2, however, three targets (A, B, and C) are shown which are not regular. The targets (shown in Column 1) have no well defined height, width, nor number of vertices. Thus, more general features are needed.

Column 2 of Figure 2 shows the three targets rotated by 10 degrees and by 90 degrees, respectively. Column 3 combines the original target, the rotated target, and the intersection. The last column shows the original target and the intersection. The hatched area in Column 4 is the area where pixels have theta-neighbors. It is easy to see that theta-neighbors may be used to distinguish among the three targets--regardless of any rotation or translation. One can simply compute a vector for an unknown target whose i-th component is the number of pixels having theta-neighbors with theta[i]. This vector is then compared to a list of similar vectors computed from the known targets. The target is classified as belonging to the class whose vector is closest to that of the unknown target.

While it is as difficult to quantify the strength of theta-neighbors as features as it is to define a typical pattern, some general results are apparent from Figure 2. First, considering 10-degree neighbors, it is noted that most of the pixels in each of the targets have 10-degree neighbors. However, the proportion of pixels with 90-degree neighbors is small for the target A, somewhat larger for the target B, and close to 1 for the target C. From this, it appears that target A may be characterized by a small proportion of pixels with theta-neighbors for theta near 90 degrees and a larger proportion as theta approaches zero. Likewise, targets similar to target C--those approaching circles--have large proportions of points with theta-neighbors for any theta (θ). The proportions for target B lie somewhere in between.

In general, a small proportion of theta-neighbors for a fixed angle indicates one of the following:

1. A radial arm subtending an angle ϕ which is less than θ (Figure 3a).

2. Several radial arms--say RA[1], RA[2],...,RA[k]--each of which subtends an angle of $\phi[i]$ with i = 1,2,...,k; which is less than θ and, when the target is rotated through the angle θ, the intersection of RA[i] and RA[j] is empty for i,j = 1,...k, and $i \neq j$ (Figure 3b).

If the proportion of pixels having theta-neighbors is near 1 for all values of θ, the shape of the target is approaching that of a circle. This leads to a second characterization of theta-neighbors. One may view the target as obtained by drawing concentric circles of radius 1,2,...,r with the common center being the center of mass, and r being the radius of the smallest pixel circle which contains the entire target. At each stage j=1,...,r, the circle of radius j is drawn, and all points on the circle which are not on the target are then erased. Thus, S[i] could be obtained by summing the pixels having a[i] neighbors on each circle of radius j = 1,2,...,r.

A second method for computing S[i]--while more complicated--revealed the relationship of theta-neighbors to area and, hence, to scale. Suppose that a circle of radius j is drawn and that no points on the arcs A[i] i=1,2,..t are points of the target. Suppose that C(A[i]) is the cardinality of A[i] and let A'[i] denote the arc obtained when A[i] is rotated by $-\theta$. Let B[i] denote $C(A[i] \cap A'[i])$. No point on any arc A[i] can be a theta-neighbor (its value is 0) and no point on A'[i] can have a theta-neighbor since the points which are theta degrees apart all have the value "0". Hence, the number of points on the circle of radius j with theta-neighbors is given by

$$2*\pi*j -(C(A[1]) +C(A'[1]) -C(B[1]) +\ldots+C(A[t])+C(A'[t]-C(B[t]))$$

Thus on a fixed circle, the number of theta-neighbors represents the proportion of that circle with theta-neighbors. If the image is scaled, these proportions remain the same since the arcs A[i] cover the same relative proportion of the circle. The features S[i] are seen to be proportional to the area of the smallest circle which can enclose the target. Furthermore, S[i]/N is an invariant where N represents the number of pixels in the smallest circle which can enclose the target.

When comparing two or more targets, the proportion they encompass of the area of the circle of radius R which inscribes them may be a significant identifying feature. For example in Figure 2, the radius of the circle needed to inscribe target A is the same as that for targets B and C. However, targets B and C will cover a larger proportion of the pixels. This is the reason for multiplying S[i] by R_0^2/R^2 rather than simply computing $S[i]/R^2$.

The results described above are summarized below as Propositions 1, 2, and 3. Essentially the claim is made that the set of features $\{F[i]|i=1,2,\ldots,n\}$ forms an invariant set of features. We present the continuous version of the proofs where "area" in the continuous case corresponds to "number of pixels" in the discrete case. Proofs for the discrete case may be obtained by substituting double sums for the double integral. The "bounded subset I of the plane" referred to in the proofs should be interpreted as "target image" in the discrete case.

Proposition 1:

Let I be a bounded subset of the plane, let θ be an angle $(0<\theta<2\pi)$, let I_θ be the subset of the plane obtained by rotating I by an angle θ about its center of mass and, for (x,y) in the plane, let (x_θ, y_θ) be the point obtained by rotating (x,y) about the center of mass of I by an angle θ. Define

$$P(x,y) = \begin{cases} 1 & \text{if } (x,y) \in I \\ 0 & \text{else} \end{cases}$$

Then if $S = \{(x,y) \in I \mid (x,y) \text{ has a theta-neighbor}\}$,
the area of S = area of $(I \cap I_\theta)$

Proof: Area of $S = \iint_S dA$

$$= \iint_I P(x,y)\, P(x_\theta, y_\theta)\, dx\, dy$$

and area of $I \cap I_\theta = \iint_{I \cap I_\theta} dA$

$$= \iint_I \chi_{I \cap I_\theta}(x,y)\, dx\, dy = \iint_I \chi_{I \cap I_\theta}(x_\theta, y_\theta)\, dx_\theta\, dy_\theta$$

Where χ is the characteristic function.

Since both integrals are over I and since each integrand is restricted to the values 0 and 1, proof of this proposition is completed if it can be shown that for any $(x,y) \in I$, the integrands are equal.

Let $(x,y) \in I$. If $P(x,y)\,P(x_\theta, y_\theta) = 1$, then $P(x,y) = 1$ and $P(x_\theta,y_\theta) = 1$, which yields $(x_\theta,y_\theta) \in I$. By definition $(x_\theta, y_\theta) \in I_\theta$; hence

$$(x_\theta, y_\theta) \in I \cap I_\theta \Rightarrow \chi_{I \cap I_\theta}(x_\theta, y_\theta) = 1$$

Similarly, if $P(x,y)\,P(x_\theta,y_\theta) = 0$, then $P(x_\theta,y_\theta) = 0$ (Recall $(x,y) \in I$), thus $(x_\theta, y_\theta) \notin I$ and hence

$$(x_\theta, y_\theta) \notin I \cap I_\theta \Rightarrow \chi_{I \cap I_\theta}(x_\theta, y_\theta) = 0$$

Therefore, the integrands are equal. The map $(x, y) \rightarrow (x_\theta, y_\theta)$ is one-to-one, and it now follows that $\iint_I dA = \iint_{I \cap I_\theta} dA$, or area of S = area of A.

Proposition 2:

The area of S is translation and rotation invariant.

Proof: Translation has the effect of moving the center of mass of I. Thus if (x,y) is the center of mass of I, the new center of mass is $(x+T_x, y+T_y)$ where T_x is the translation in the x direction and T_y is the translation in the y direction. The change of variables x to $(x+T_x)$ and y to $(y+T_y)$ and Proposition 1 shows S for the translated image equals S for the original image I.

For rotation, suppose I has been rotated by ϕ to form I_ϕ. By Proposition 1, areas of S = area of $(I \cap I_\theta)$

= area of $(I \cap I_{\phi+\theta})$

= area of S for I_θ

<u>Proposition 3</u>:

Let I be a bounded subset of the plane and let kI denote the subset of the plane obtained when I is scaled by k in both the x and y directions. Let R denote the radius of the smallest circle centered at (X, Y) which can inscribe I and let R_k denote the radius of the smallest circle which can inscribe kI, and let S denote the set of points in I with theta-neighbors.
Then

$$\frac{area\ of\ S}{R^2} = \frac{area\ of\ kS}{R_k^2}$$

<u>Proof</u>: (areas of S)/R^2 is simply πp where p is the proportion of the circle of radius R which is covered by $I \cap I_\theta$. Since I is scaled uniformly to form kI, this proportion must be preserved for any scaling. Thus

$$\frac{area\ of\ kS}{R_k^2} = \pi P = \frac{area\ of\ S}{R^2}$$

The above propositions seem to indicate that--at least in 2-D space--the problem of target classification can be solved by judiciously choosing a set {theta[1],theta[2]..,theta[n]} of angles and comparing the feature vector (F[1],F[2],..,F[n]) from an unknown target to a list of feature vectors of known targets and classifying by nearest neighbor. As shown previously by Fuller (1990),[1] this is not practical when dealing with digitized images due to aliasing, jaggies, and other problems inherent in computer graphics. It was also shown that even such simple measurements as target area or length of line segment are not preserved under affine transformations carried out on computer. Furthermore, it was the goal of this study to not only solve the problem of target recognition in 2-D, but also to develop a methodology which was readily extendable to three dimensions (3-D). Therefore, an attempt was made to develop a neural network based recognition system.

HYBRID NEURAL NETWORK ALGORITHM

Neural network technology provides a number of tools which form the basis for a potentially fruitful approach to the recognition problem. It provides powerful collective and computational techniques for designing a robust ATR system. The ANS model described in this report implements a novel pattern recognition process to demonstrate invariant pattern recognition, robustness to noise, obscuration and camouflage.

The elements that combine to determine system performance are spatial resolution of the sensor, the features extracted from signatures, the structure of the classifier, and the ANS. With an ANS, important issues are optimizing the network structure in terms of the learning algorithm and the number of connections.

Regardless of any 2-D affine transformation, the extension to 3-D is dependent on the development of a network capable of associating any of the rotations about the vertical (i.e., z) axis with the appropriate target class. In addition, the network had to be capable of generalizing. This means it had to be capable of interpolation to identify targets rotated in the x-y plane at angles between those presented in the training set. It also had to be able to identify those targets within a class which are similar. It was desired that the network use a minimal number of neurons so that any generalization taking place would be apparent from the test results. Thus, emphasis during the training and testing of the network was on three issues: (1) ability to generalize; (2) minimum number of neurons; and (3) accuracy.

In addition, the following two problems need to be addressed:

1. A target at one angle of rotation about the vertical axis might bear little or no resemblance to the same target at another angle of rotation.

2. A target at some angle of rotation about the vertical axis might bear a strong resemblance to another target at the same or a different angle.

The hybrid neural net model is based on the Cluster Euclidean Network described by Hartigan (1975),[2] Kohonen's (1987)[3] Learning Vector Quantization (LVQ), and Adaptive Resonance Theory (Lippman, 1987).[4] The network is shown schematically in Figure 4. Initially, the network consists of one neuron whose node center is a vector whose i-th component is F[i] (number of pixels with theta[i]-neighbors) for the first target in the training set. This neuron has a sphere of influence set at some large value--say v[0]. As more examples are presented to the network, the following steps are taken:

1. The radius of the sphere of influence of a neuron may be decreased. This occurs if a training example not of the type represented by the neuron falls within the influence of that

neuron. If v(t) represents this radius at time t, the radius is updated by

$$v(t+1) = v(t)*(1-\alpha[1](t))$$

where $\alpha[1]$ is a small real number which gradually decreases to 0 as t increases. In addition, comparable success was obtained by using

$$v(t+1) = v(t)*k$$

where k is some constant near 1.

2. The node center of the neuron is adjusted in the manner described by Kohonen (1987).[3] This allows the node center of the neuron to seek the statistical center of the data represented by that neuron. Thus if nc(t) represents the node center at time t and X is the training vector, then

$$nc(t+1) = nc(t) + \alpha[1](t)*(X - nc(t))$$

if classification is correct.

$$nc(t+1) = nc(t) - \alpha[2](t)*(X - nc(t))$$

if classification is incorrect.

Though not necessary, it is desirable that $\alpha[1] = \alpha[2]$.

The above equations show that a neuron which fires incorrectly has both its radius of influence decreased and its node center shifted.

3. A new neuron may be added. This occurs if a training example does not fall within the influence of any currently active neuron and if nearest neighbor classification of the training example is incorrect. When the new neuron is added, the features of its node center are set to the values of the training example and its radius of influence set to v[0].

In addition, if the training set is finite, logic can be included to ensure that all neurons identify at least one member of the training set. A neuron may identify no pattern if the updating procedure pushes the node center too far away from the data early in the training. If the neuron does not fire for any training pattern, it is disabled and reused--if needed--at a later time.

Since the input space is bounded and is finite, the network is stable. Thus (1) only a finite number of clusters can be formed, and (2) the node centers reach a steady state. Thus, if nc[i] is the node center of the i-th active neuron, then

$$nc[i] \rightarrow nc[f][i] \text{ as } \alpha[2] \rightarrow 0$$

where nc[f][i] represents the steady state values of neuron i. Furthermore, the network is dynamic since new patterns may be added at any time.

During testing, the unknown target has its features extracted and compared to the node centers of all active neurons. Let v[i] denote the radius of the sphere of influence of an active neuron i and let X denote the feature vector of the unknown target. The input is classified as belonging to class i if and only if

$$d(X,nc[f][i]) < v[i]$$

where d represents Euclidean distance,
or if and only if

$$d(X,nc[f][i]) > v[i]$$

where d represents the dot product of nc[f][i] and X divided by the product of norm(X) multiplied by norm(nc[f][i]), that is

$$d(X,nc[f][i]) = \langle nc[f][i],X \rangle \;/\; \|X\| * \|(nc[f][i]\|$$

Preliminary training and testing have been completed in an experiment designed to determine if the methodology described above can be successful in performing invariant 3-D target recognition. Training and testing were performed on real data obtained from five targets presented at 105 different orientations each in space. Preliminary results showed that the ANS converged rapidly, target recognition accuracy of over 86 percent was achieved (Holland, 1991).[5] Additionally, previous work revealed that the network was able to recognize the targets even in the noisy environment.

CONCLUSIONS

A novel set of affine invariant features and an artificial neural net model were described. Preliminary results showed that the hybrid ANS model converged rapidly, and the network was able to recognize some noisy targets with a high degree of accuracy. This target recognition approach demonstrates that using an ANS architecture, recognition can be obtained independent of orientation, size, or aspect angle. Results of the experimental studies on performance characteristics of the features and the ANS recognizer are under investigation and will be published in the near future.

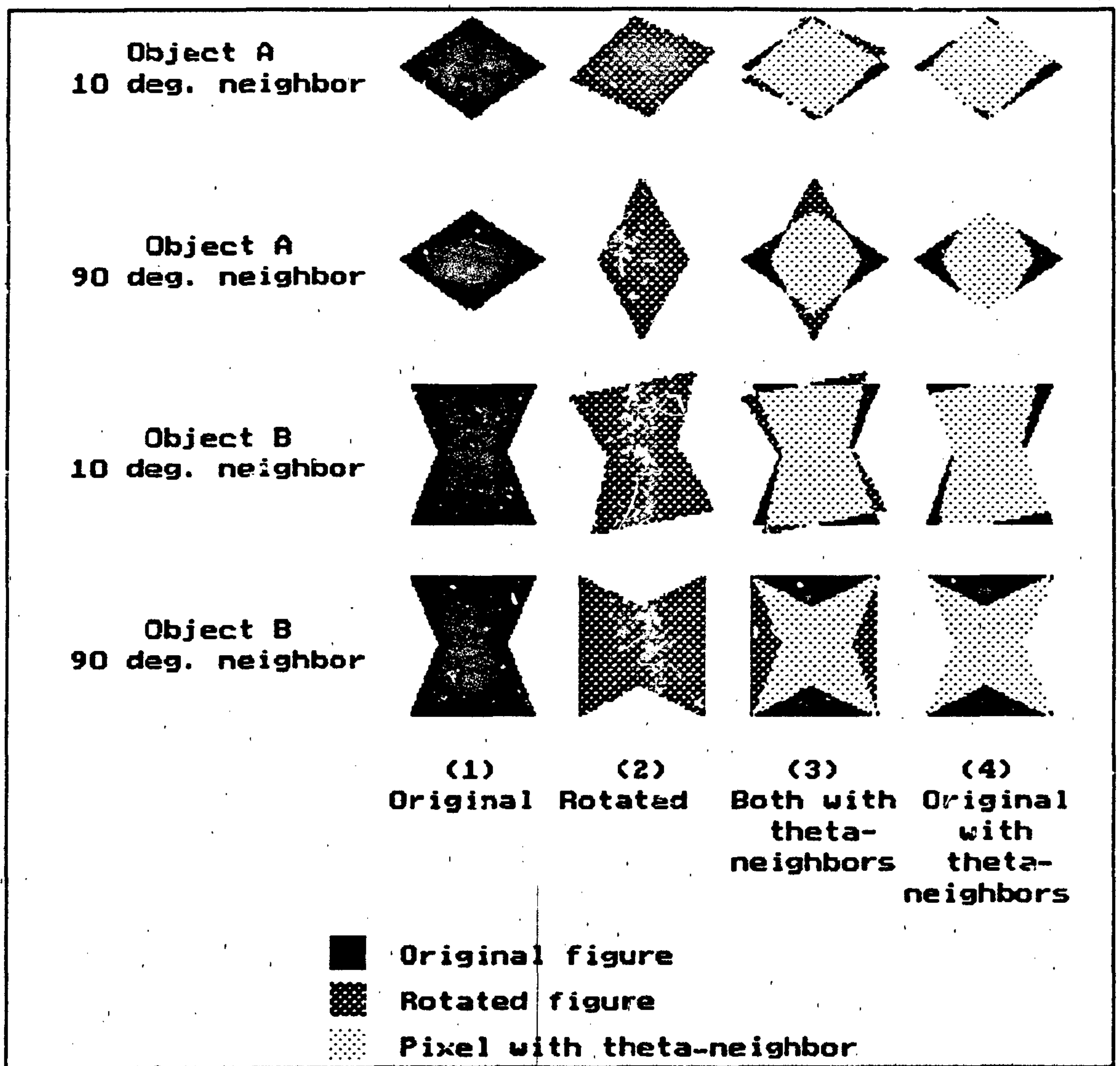

FIGURE 1. THETA-NEIGHBORS OF TWO SIMPLE GEOMETRIC OBJECTS

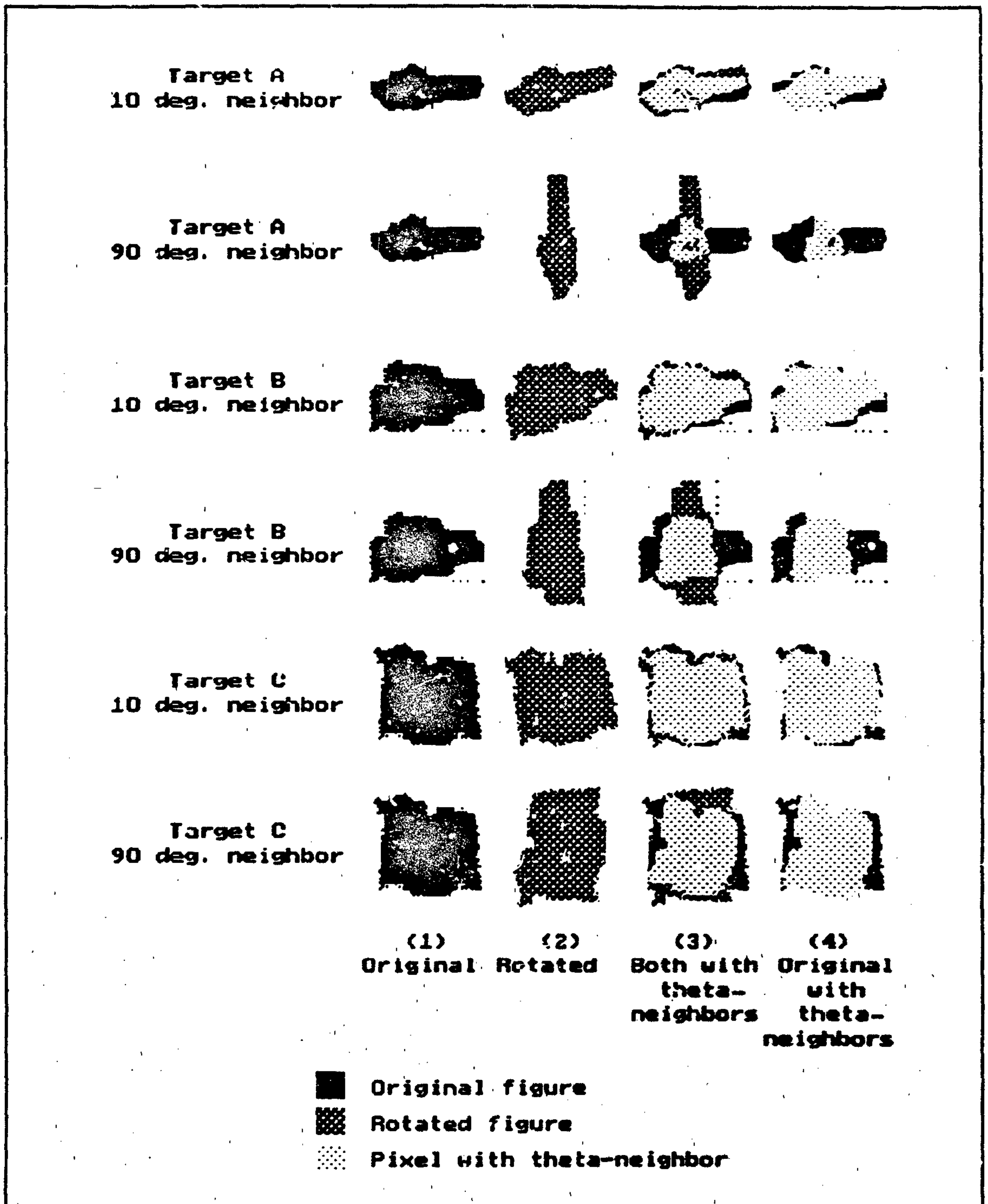

FIGURE 2. THETA-NEIGHBORS OF THREE FIELD TARGETS

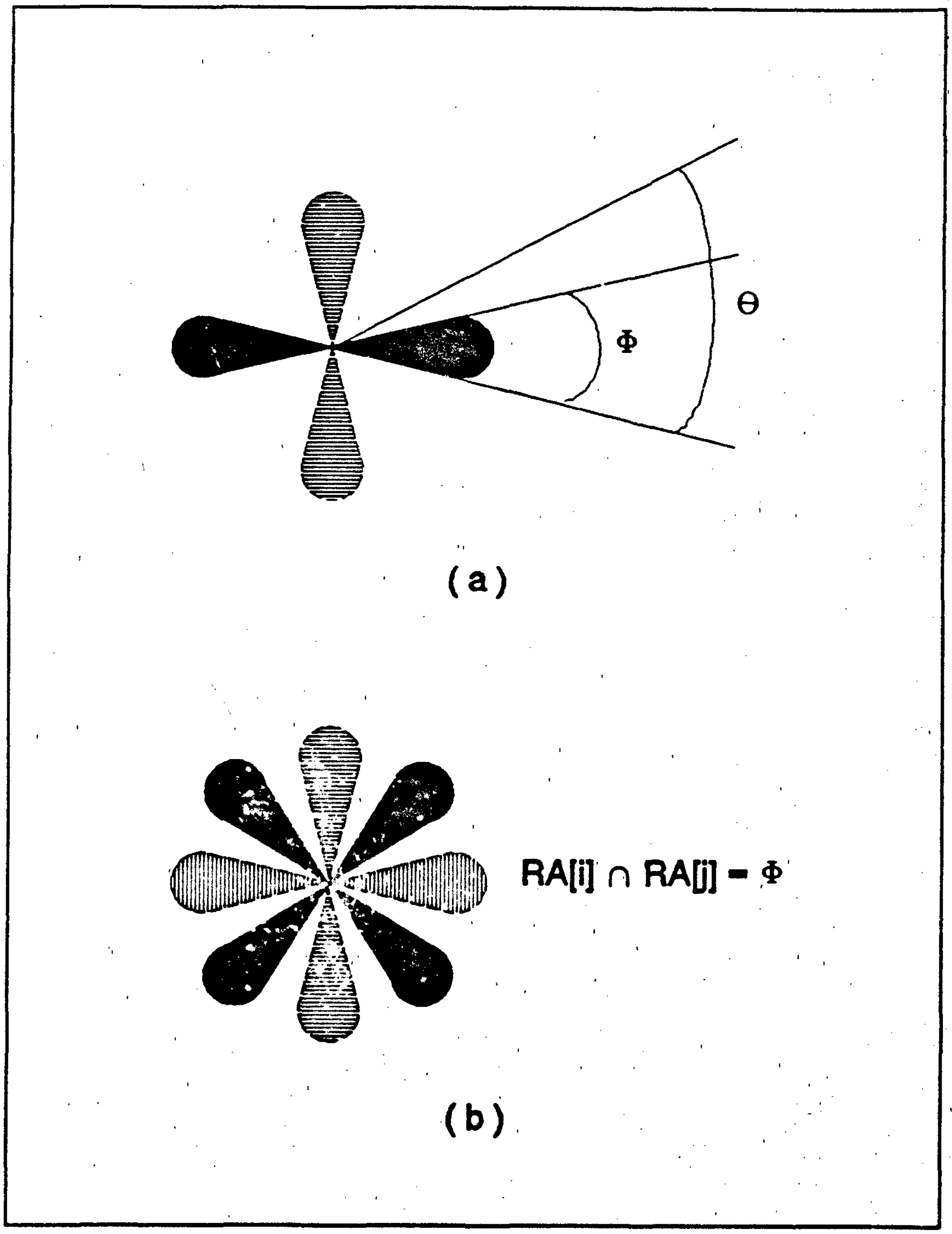

FIGURE 3. VARIATIONS OF THETA-NEIGHBOR ANGLES

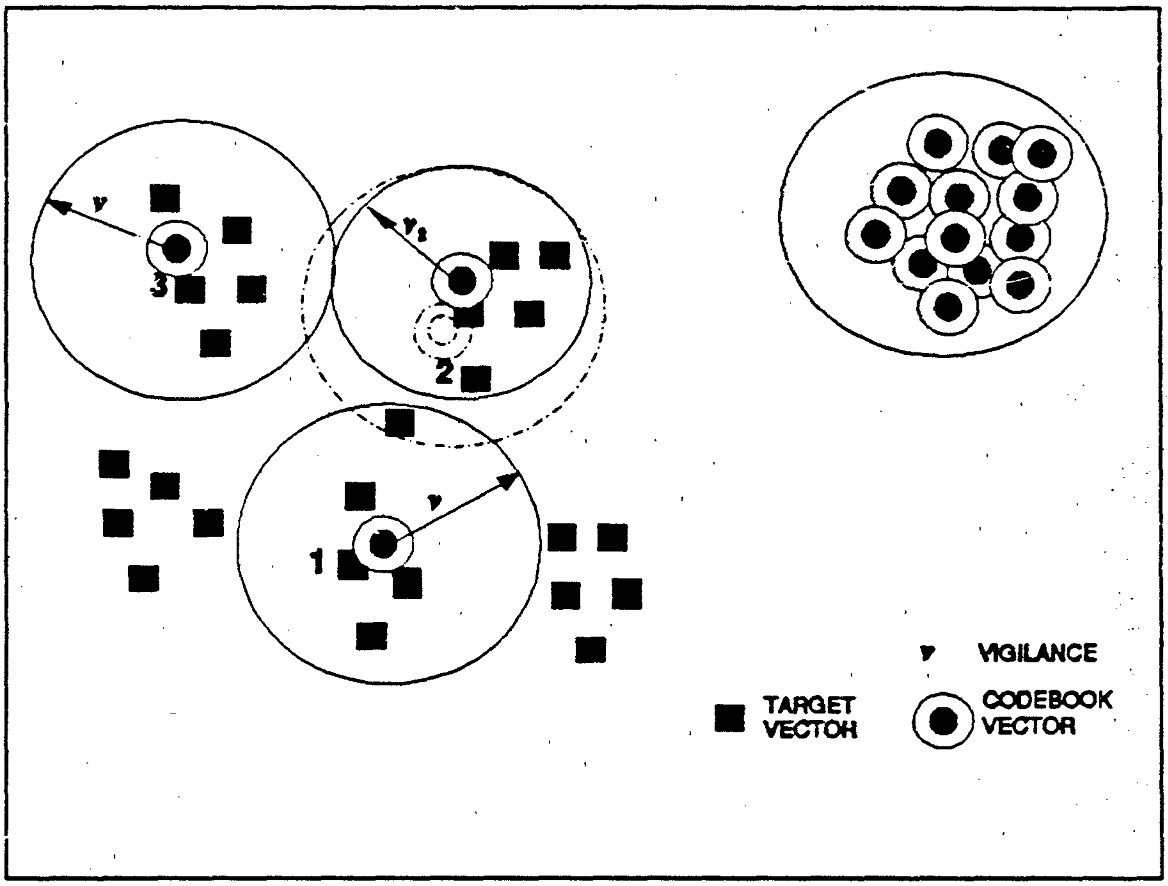

FIGURE 4. THE HYBRID NEURAL MODEL FEATURE SPACE

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